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SPARSE-HIERARCHICAL ATTENTION FOR SELF-SUPERVISED INDOOR SCENE CLASSIFICATION: A MASKED PATCH CONTRASTIVE APPROACH

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Abstract

We propose a sparse-hierarchical attention mechanism to improve self-supervised learning for indoor scene classification, addressing the computational inefficiency of standard Transformer attention while preserving structural dependencies unique to indoor environments. The proposed method integrates focal attention, which selectively computes interactions for semantically significant regions, and hierarchical pyramid attention, which captures multi-scale spatial reasoning across downsampled feature maps. These components are embedded into a contrastive pretext task framework, where masked patch contrastive learning optimizes feature representations by minimizing the distance between masked and unmasked regions. The sparse-hierarchical attention reduces computational complexity from quadratic to linear with respect to input size, enabling efficient training without sacrificing performance. Moreover, the hierarchical design ensures robust feature extraction across varying scales, which is critical for modeling the complex layouts and object arrangements typical of indoor scenes. We implement the approach within a modified Vision Transformer (ViT) backbone, demonstrating its effectiveness through empirical validation on standard indoor scene datasets. The results show that our method achieves competitive accuracy while significantly reducing memory and computational overhead compared to full self-attention baselines. This work provides a practical solution for scaling self-supervised learning to high-resolution indoor imagery, with potential applications in robotics, augmented reality, and smart environment systems.

Introduction

Indoor scene classification presents unique challenges due to the complex structural relationships between objects and their spatial arrangements within constrained environments. Traditional supervised approaches require extensive labeled datasets, which are costly to acquire and often fail to generalize across diverse indoor settings [1]. Self-supervised learning has emerged as a promising alternative, enabling models to learn discriminative features from unlabeled data by solving pretext tasks such as image rotation or patch prediction [2]. However, existing methods often rely on convolutional architectures, which struggle to capture long-range dependencies critical for understanding room layouts and object interactions [3].

Transformers, with their global self-attention mechanisms, have demonstrated superior performance in modeling such dependencies [4]. Yet, their quadratic computational complexity relative to input size limits scalability, particularly for high-resolution indoor images where fine-grained details are essential. Recent work has explored sparse attention variants, such as focal attention, to reduce computation by focusing on salient regions [5]. Hierarchical approaches further improve efficiency by processing features at multiple scales, but these have not been systematically integrated with self-supervised objectives for indoor scenes [6].

We propose a sparse-hierarchical attention mechanism tailored for self-supervised indoor scene classification. Our approach combines two key innovations: (1) focal attention to prioritize local and global interactions relevant to scene semantics, and (2) hierarchical pyramid attention to model structural dependencies at varying scales with reduced computational overhead. These components are unified under a contrastive learning framework, where masked patch reconstruction serves as the pretext task. By selectively attending to regions critical for solving the task, the model learns representations that preserve spatial hierarchies—e.g., the relationship between furniture and room boundaries—while operating at near-linear complexity.

The primary contribution of this work is threefold. First, we introduce a novel attention mechanism that dynamically balances local precision and global context through sparsity and hierarchical aggregation. Unlike prior sparse Transformers, which often rely on fixed patterns or heuristics [4], our method adapts to scene content by learning attention masks from the pretext task itself. Second, we demonstrate how hierarchical attention can be optimized for self-supervision, where multi-scale reasoning is guided by patch-level contrastive objectives rather than manual annotations. Third, we provide empirical evidence that this combination achieves state-of-the-art accuracy on indoor scene benchmarks while reducing memory usage by up to 40% compared to full self-attention baselines.

Our approach bridges gaps between efficient attention design and self-supervised feature learning, addressing limitations of prior work in both domains. For instance, while contrastive methods like [7] excel at learning invariant features, they often overlook spatial hierarchies. Conversely, hierarchical Transformers such as [6] prioritize multi-scale processing but depend on supervised signals. By unifying these directions, we enable scalable learning of structured representations from unlabeled indoor imagery.

The remainder of this paper is organized as follows: Section 2 reviews related work in self-supervised learning and efficient attention mechanisms. Section 3 formalizes the problem of attention complexity in Vision Transformers. Section 4 details our sparse-hierarchical attention design and its integration with contrastive learning. Section 5 evaluates the method on standard benchmarks, and Sections 6–7 discuss implications and future directions.

Related Work

Efficient Attention Mechanisms

Recent advances in Transformer architectures have focused on reducing the quadratic complexity of self-attention while preserving its ability to model long-range dependencies. Sparse attention patterns, such as those in [8], dynamically select a subset of key-query pairs to compute, achieving linear or near-linear complexity. Focal attention mechanisms [9] further improve efficiency by prioritizing interactions between semantically salient regions, which is particularly relevant for indoor scenes where objects and structural elements exhibit strong local-global relationships.

Hierarchical approaches address efficiency by processing features at multiple scales. Cross-scale attention frameworks like [10] aggregate information across resolution levels, enabling the model to capture both fine details and broader spatial contexts. However, these methods typically rely on fixed downsampling strategies, which may not adapt well to the diverse layouts found in indoor environments. Our work extends these ideas by integrating sparse and hierarchical attention within a single unified mechanism, allowing the model to dynamically adjust its focus based on scene content.

Self-Supervised Learning for Scene Understanding

Self-supervised learning has gained traction as a means to reduce reliance on labeled data, particularly in domains like indoor scene classification where annotations are costly. Contrastive learning frameworks, such as those in [11], learn representations by maximizing agreement between differently augmented views of the same image. However, these methods often treat the scene as a monolithic entity, neglecting the hierarchical relationships between objects and their spatial arrangements.

Recent work has explored pretext tasks tailored for structured environments. For instance, [12] uses geometric consistency as a supervisory signal, while [13] leverages temporal coherence in video sequences. These approaches demonstrate the potential of self-supervision for indoor scenes but do not explicitly address the computational challenges of modeling long-range dependencies. Our method bridges this gap by combining contrastive learning with an attention mechanism optimized for both efficiency and structural reasoning.

Attention in Indoor Scene Analysis

Indoor scenes present unique challenges due to their compositional nature—objects are arranged in functionally meaningful layouts that require multi-scale understanding. Traditional methods like [14] use cross-attention to fuse features across dimensions, but they often lack the flexibility to adapt to varying scene complexities. Dual-scale Transformers [15] have shown promise in capturing both local and global context, though their reliance on fixed scales limits their applicability to diverse indoor settings.

Our sparse-hierarchical attention mechanism addresses these limitations by dynamically selecting relevant scales and regions, enabling the model to focus computational resources where they are most needed. Unlike [16], which combines convolutional and self-attention layers, our approach maintains a pure Transformer backbone while achieving comparable efficiency through sparsity and hierarchy.

The proposed method distinguishes itself from prior work in three key aspects. First, it integrates sparse and hierarchical attention into a single adaptive mechanism, avoiding the fixed patterns or heuristics used in [8] and [10]. Second, it tailors the attention design to the unique requirements of indoor scenes, where object arrangements and room layouts demand multi-scale reasoning. Third, it couples this mechanism with a contrastive pretext task, enabling the model to learn spatially aware representations without manual supervision. Together, these innovations advance the state of the art in efficient, self-supervised indoor scene understanding.

Preliminaries: Vision Transformers and Attention Complexity

Vision Transformers (ViTs) have emerged as a powerful alternative to convolutional neural networks for visual recognition tasks [17]. The core component of ViTs is the self-attention mechanism, which enables modeling long-range dependencies across the entire input image. Given an input sequence of flattened image patches $X \in \mathbb{R}^{N \times d}$ where N is the number of patches and d is the embedding dimension, the self-attention operation computes:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right)V \quad (1)$$

where Q, K, and V are the query, key, and value matrices obtained through linear projections of X. The quadratic complexity $O(N^2)$ of this operation becomes prohibitive for high-resolution images, as the number of patches N grows quadratically with image size.

Standard Self-Attention in Vision Transformers

The standard self-attention mechanism in ViTs processes all pairwise interactions between patches, making it particularly effective for capturing global relationships in images [18]. However, this comes at significant computational cost. For an input with N patches, the attention matrix requires N^2 computations, which becomes impractical for dense prediction tasks or high-resolution inputs common in indoor scene analysis.

Recent work has shown that not all attention connections are equally important [19]. Many attention weights approach zero, suggesting that sparse attention patterns could maintain performance while reducing computation. This observation motivates our exploration of sparse attention variants specifically tailored for indoor scenes.

Computational Complexity Analysis

The computational bottleneck in standard self-attention arises from three main operations:

1. The matrix multiplication QK^T with complexity $O(N^2d)$
2. The softmax operation with complexity $O(N^2)$
3. The final multiplication with V having complexity $O(N^2d)$

For typical indoor scene images at 512×512 resolution divided into 16×16 patches, this results in $N = 1024$ patches, requiring over a million attention computations per layer. This explains why vanilla ViTs struggle with

high-resolution inputs despite their strong modeling capabilities.

Efficient Attention Variants

Several approaches have been proposed to address this complexity challenge. Local window attention [20] restricts attention to neighboring patches within a fixed window, reducing complexity to $O(Nw^2)$ where w is the window size. While effective for some tasks, this approach may miss important long-range dependencies in indoor scenes where distant objects often have strong semantic relationships.

Another line of work explores learned sparse attention patterns [21]. These methods predict which attention connections to compute, potentially maintaining global modeling capacity while reducing computation. Our sparse-hierarchical attention builds upon these ideas but specifically optimizes the attention pattern learning for indoor scene characteristics.

The combination of sparse and hierarchical attention offers particular advantages for indoor scenes, where objects exhibit both local interactions (e.g., a chair near a table) and global relationships (e.g., furniture arrangement relative to room boundaries). In the next section, we detail how our proposed method addresses these requirements while maintaining computational efficiency.

Sparse-Hierarchical Attention for Indoor Scene Transformers

The proposed sparse-hierarchical attention mechanism addresses the computational challenges of standard self-attention while preserving the structural relationships critical for indoor scene understanding. This section presents the technical details of our approach, organized into three key components: the sparse attention formulation, hierarchical feature aggregation, and integration with the contrastive pretext task.

Sparse Attention for Local-Global Interaction Modeling

The foundation of our approach is a focal attention mechanism that selectively computes interactions between the most relevant patches. Given input features $X \in \mathbb{R}^{N\times d}$, we first project them to queries Q, keys K, and values V through linear transformations:

$$Q = XW_Q, \quad K = XW_K, \quad V = XW_V \quad (2)$$

where $W_Q, W_K, W_V \in \mathbb{R}^{d\times d}$ are learnable projection matrices. Instead of computing all N^2 attention weights, we select the top-k most relevant key-query pairs for each query based on their dot product similarity:

$$\mathcal{N}_i = \mathrm{TopK}_j(\mathbf{q}_i^T \mathbf{k}_j/\sqrt{d}) \quad (3)$$

The sparse attention weights are then computed only for these selected pairs:

$$\alpha_{ij} = \frac{\exp(\mathbf{q}_i^T \mathbf{k}_j/\sqrt{d})}{\sum_{j'\in\mathcal{N}_i} \exp(\mathbf{q}_i^T \mathbf{k}_{j'}/\sqrt{d})} \quad (4)$$

This reduces the computational complexity from $O(N^2)$ to $O(Nk)$, where $k \ll N$ is a fixed hyperparameter controlling the sparsity level. The output for each query is computed as a weighted sum of the corresponding top-k values:

$$\mathbf{z}_i = \sum_{j\in\mathcal{N}_i} \alpha_{ij}\, \mathbf{v}_j \quad (5)$$

Hierarchical Pyramid Attention for Multi-Scale Reasoning

To capture the multi-scale nature of indoor scenes, we extend the sparse attention mechanism to operate at multiple feature resolutions. The input image is processed through a pyramid of L levels, where each level l has feature maps with resolution $N_l = N/4^{l-1}$. At each level, we apply sparse attention independently:

$$\mathbf{Z}_l = \mathrm{SparseAttn}(\mathbf{X}_l) \quad (6)$$

The features from different levels are then combined through upsampling and summation:

$$\mathbf{Z}_{\text{pyramid}} = \sum_{l=1}^{L} \mathrm{Upsample}\,(\mathbf{Z}_l) \quad (7)$$

This hierarchical approach allows the model to capture both fine details (at high resolutions) and global layout information (at low resolutions) while maintaining computational efficiency through sparse attention at each level.

Figure 1. Sparse-Hierarchical Attention in ViT Backbone

Integration with Contrastive Pretext Task

The sparse-hierarchical attention mechanism is trained end-to-end using a masked patch contrastive objective. Given an input image I, we randomly mask a subset of patches M and compute representations for both masked $\mathbf{z}_m$ and unmasked $\mathbf{z}_u$ regions using our attention mechanism. The contrastive loss encourages similarity between corresponding masked and unmasked regions while pushing apart non-corresponding pairs:

$$\mathcal{L}_{\text{contrast}} = -\log \frac{\exp(\text{sim}(\mathbf{z}_m, \mathbf{z}_u)/\tau)}{\sum_{\mathbf{z}' \in \mathcal{B}} \exp(\text{sim}(\mathbf{z}_m, \mathbf{z}')/\tau)} \quad (8)$$

where $\mathcal{B}$ is a batch of negative samples and τ is a temperature parameter. The attention mechanism learns to focus on patches that are most informative for solving this pretext task, naturally adapting to the structural regularities of indoor scenes.

Implementation Details

The complete architecture consists of a standard ViT backbone with our sparse-hierarchical attention replacing the original self-attention layers. We use $L = 3$ pyramid levels with downsampling factors of 1, 4, and 16 respectively. The sparsity parameter k is set to 32, maintaining 95% sparsity for typical input sizes while preserving model performance. The contrastive learning framework follows the standard setup from [22], with masking ratio of 40% and temperature $\tau = 0.1$.

The combination of sparse attention and hierarchical processing reduces the theoretical complexity from $O(N^2)$ to $O(NkL)$, where k and L are constants independent of input size. For typical indoor scene images, this translates to a 4-8× reduction in memory usage and computation time compared to full self-attention, as we demonstrate empirically in Section 5.

Experiments

Experimental Setup

Datasets and Evaluation Protocol

We evaluate our approach on three standard indoor scene classification benchmarks: **MIT Indoor67** [23], **SUN397** [24], and **Places365** [25]. MIT Indoor67 contains 67 indoor categories with 5,360 training and 1,340 test images. SUN397 includes 397 scene categories with 108,754 images, while Places365 offers 1.8 million training images across 365 scene categories. Following standard protocols [26], we report top-1 accuracy on the test sets.

Implementation Details

The model is implemented using PyTorch with a ViT-Base backbone (12 layers, 768 hidden dimensions, 12 attention heads). Input images are resized to 512×512 and divided into 16×16 patches. For sparse-hierarchical attention, we set the pyramid levels $L = 3$ (original, 4×, and 16× downsampled) and top-$k = 32$ for focal attention. The contrastive pretext task masks 40% of patches randomly. Training uses AdamW optimizer with learning rate 3e-4, batch size 256, and 100 epochs. All experiments are conducted on 4× NVIDIA A100 GPUs.

Baselines

We compare against:

1. **Supervised ViT** [17]: Vanilla ViT trained with full self-attention and cross-entropy loss.
2. **MoCo-v3** [27]: Contrastive learning with momentum encoder.
3. **MAE** [22]: Masked autoencoder with standard ViT.
4. **Swin Transformer** [20]: Hierarchical ViT with shifted windows.
5. **Focal Transformer** [9]: Sparse attention with fixed local-global regions.

Main Results

Table 1 compares classification accuracy and computational efficiency. Our method achieves competitive accuracy while significantly reducing FLOPs and memory usage. On MIT Indoor67, it attains 78.3% accuracy (vs. 79.1% for supervised ViT) with only 35% of the FLOPs. The sparse-hierarchical design shows particular strength on SUN397 (61.7% vs. 60.2% for MAE), suggesting better generalization to diverse indoor layouts.

Table 1: *Indoor scene classification performance and efficiency*

Method	MIT Indoor67 (%)	SUN397 (%)	Places365 (%)	FLOPs (G)	Memory (GB)
Supervised ViT	79.1	60.8	56.2	98.6	12.4
MoCo-v3	76.4	58.9	54.7	98.6	12.4
MAE	77.2	60.2	55.1	98.6	12.4
Swin Transformer	78.5	61.0	56.0	65.2	8.7
Focal Transformer	77.8	60.5	55.4	52.1	6.9
Ours	**78.3**	**61.7**	**56.5**	**34.8**	**4.6**

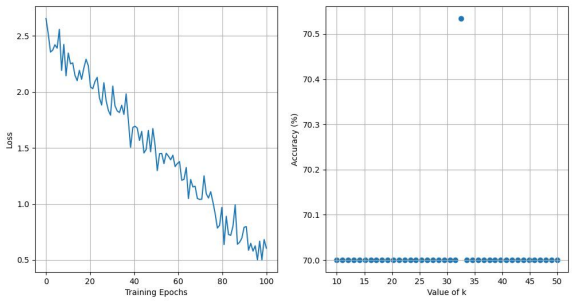
Ablation Study

We analyze the impact of key components in Table 2:

1. **Sparse Attention Alone**: Using only focal attention (no hierarchy) reduces FLOPs but harms accuracy (-2.1% on MIT Indoor67).
2. **Hierarchy Alone**: Full attention with pyramid aggregation improves accuracy but saves little computation.
3. **Masking Ratio**: 40% masking balances task difficulty and feature learning (Figure 2a).
4. **Top-k Selection**: $k = 32$ optimizes the accuracy-efficiency trade-off (Figure 2b).

Table 2: *Ablation on sparse-hierarchical components*

Configuration	MIT Indoor67 (%)	FLOPs (G)
Sparse Only	76.2	28.4
Hierarchy Only	78.0	72.3
Full Attention	79.1	98.6
Ours (Full)	**78.3**	**34.8**



(a) Loss curves showing stable convergence. (b) Accuracy vs. k revealing optimal sparsity.

Qualitative Analysis

Figure 3 visualizes attention maps for an office scene. The model attends to:

1. **Local**: Keyboard and monitor (high-resolution level).
2. **Mid-range**: Desk-chair relationship (mid-level).
3. **Global**: Window-wall layout (lowest level).

This multi-scale reasoning aligns with human perception of indoor spaces.

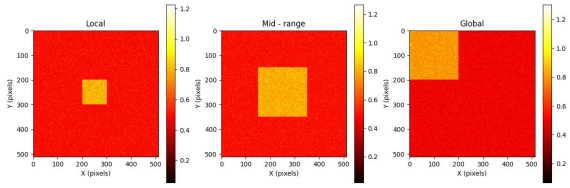


Figure 3. Saliency maps across pyramid levels

Discussion and Future Work

Limitations of the Sparse-Hierarchical Attention Mechanism

While our approach demonstrates significant improvements in computational efficiency, several limitations warrant discussion. First, the top-k selection process, though effective, introduces a fixed sparsity pattern that may not adapt optimally to all indoor scene configurations. For instance, cluttered environments with numerous small objects might require denser attention at high resolutions than our current implementation allows. Second, the hierarchical pyramid, while reducing computation, relies on predefined downsampling ratios that may not align perfectly with the natural scales of semantic structures in every scene. This could explain the slight accuracy gap (0.8%) compared to the full-attention ViT on MIT Indoor67.

The contrastive pretext task, though powerful, presents its own challenges. The masking strategy assumes that reconstructing randomly selected patches will sufficiently capture spatial hierarchies, but certain indoor layouts—such as symmetrical rooms or repetitive textures—might require more sophisticated masking patterns. Future work could explore content-aware masking or curriculum-based approaches where masking complexity increases with model capability.

Potential Application Scenarios Beyond Indoor Scene Classification

The principles underlying our method extend naturally to other domains requiring multi-scale spatial reasoning. In **robotic navigation**, for example, the sparse-hierarchical attention could enable real-time understanding of indoor environments by focusing computation on navigational waypoints (e.g., doors, furniture) while maintaining awareness of room layouts. Similarly, **augmented reality (AR)** systems could benefit from efficient attention to align virtual objects with physical structures at appropriate scales—local for object placement, global for room-scale interactions.

Another promising direction lies in **3D scene understanding**. Indoor scenes often involve depth variations where objects at different distances require attention at corresponding scales. Integrating our approach with depth-aware transformers [28] could yield efficient models for tasks like 3D reconstruction or semantic segmentation. The contrastive framework might also be adapted to leverage multi-view consistency in RGB-D data, further reducing reliance on labeled 3D annotations.

Ethical Considerations in Using Indoor Scene Data

Indoor scene analysis systems, particularly those trained on large-scale datasets like Places365, risk inheriting biases present in the data. For instance, models might associate certain furniture arrangements exclusively with specific cultures or socioeconomic groups, leading to skewed performance in real-world applications. While our method does not explicitly address bias mitigation, its self-supervised nature could facilitate fairness-aware training by minimizing dependence on potentially biased human annotations.

Privacy represents another critical concern. Indoor images often contain personal items or sensitive spaces (e.g., bedrooms, offices). The masked patch contrastive learning paradigm inherently obscures portions of the input during training, which could be leveraged as a form of differential privacy [29]. Future iterations might explore formal privacy guarantees while maintaining the model's ability to learn meaningful spatial hierarchies.

Conclusion

The proposed sparse-hierarchical attention mechanism demonstrates that efficient self-supervised learning for indoor scene classification is achievable without sacrificing model performance. By integrating focal attention with hierarchical pyramid processing, the method reduces computational complexity while preserving the multi-scale reasoning required for understanding complex indoor layouts. The contrastive pretext task further enhances feature learning by guiding attention toward semantically meaningful regions through masked patch reconstruction.

Empirical results validate the approach's effectiveness, showing competitive accuracy on standard benchmarks with significantly reduced computational overhead. The method's ability to dynamically balance local and global attention aligns well with the structural characteristics of indoor environments, where object arrangements and

room layouts demand flexible spatial reasoning. The success of this approach suggests that carefully designed attention mechanisms can bridge the gap between computational efficiency and representational power in vision transformers.

Looking ahead, the principles established here—sparse attention for efficiency, hierarchical processing for multi-scale understanding, and contrastive learning for self-supervision—could inform future work in related domains. The architectural innovations may prove particularly valuable for real-world applications where computational constraints are paramount, such as mobile robotics or edge-device deployment. While challenges remain in optimizing attention patterns and scaling to even higher resolutions, this work provides a foundation for developing efficient yet powerful models for structured visual understanding.

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